# Optimization Algorithms Inspired by Biological Ants and Swarm Behavior

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## Abstract

Ants are simple creatures that inspire many researchers in the field of Computer Science to develop new solutions for optimization and artificial intelligence problems. Some aspects of ant behavior can be implemented in a computer environment in order to solve a particular problem or to derive emergent behavior similar to ant colonies behavior. In this paper we give a brief overview of some functions of biological ants and the colony behavior generated from the interaction of a swarm of ants. Following we review the main existing work from the main researchers in the field on applying the ant metaphor in solving hard combinatorial optimization problems.

## 1. Introduction

Compared to humans, an individual ant has very little brain power. While humans have approximately 10 billion neurons, ants have only 250,000 [3]. One may ask how they can perform such astonishing tasks when in collective body. The real power of ants resides in their colony brain. The self-organization of those individuals is very similar to the organization found in brain-like structures, as indicated by *Victorino Ramos* [23]. Even though the individuals of a swarm are limited in number of neurons, an average ant colony of 40.000 ants would have approximately the same number of neural cells as any human, approximately 10 billion.

Like neurons, ants use mainly chemical agents to communicate; one ant releases a molecule of pheromone that will influence the behavior of other ants (stigmergy). When we learn something new, connections are created in our brain, and as we repeatedly use that information, the number of neurotransmissors and neuroreceptors used in synapses related to that process are reinforced. Similarly, when one ant traces a pheromone trail to a food source, that trail will be used by many other ants that will reinforce that trail even more (autocatalytic process).

This paper is intended introduce the reader to the subject of ant algorithms and demonstrate that simple agents working together can produce complex behavior. The organization of the next sections is as follow: section 1.1 gives an overview of some properties of ant behavior that are important to our work. We are mainly concerned on how real world ants implement the solution of searching for food and how they interact to transport it from the found location to their nest, in the shortest possible time. This simple task involves several complex tasks such as navigation, communication and self-organization. Section 2 is focused on showing the current research on Artificial Ant Algorithms with the work of *Dorigo et. al* [10]-[22] and his contributions to the field. Artificial Intelligence (and even Computer Science) is still in its early stages of maturity compared with other types of science. Artificial Ant Systems is an even newer field and still has a great amount of work to be done.

## 1.1. The Real World Ants

In the insect world, ants along with other members of the Hymenoptera order (which includes bees and wasps) are known to show the most complex social behavior in the insect world [5]. As said earlier, they depend on the collectiveness of their colonies to achieve vital tasks as defense, feeding, nest maintenance and reproduction.

Complete behavioral understanding of ant and ant colonies is far from being achieved, but several researchers dedicated several years researching important aspects of this species, including their behavior. In this paper, we will only approach some of the properties of biological ant's behavior that may somehow serve as an inspiration source for computer scientists to develop novel techniques in the field of artificial intelligence.

**Competition and the environment**

Ants are not isolated species neither live in a simple environment. The environment they live in greatly contributes to the behavior presented by an ant colony. Dr. Deborah Gordon [8] spent many years in the Arizona desert studying red harvester ants *(Pogonomyrmex barbatus)* and one of the observations Dr. Gordon made is very interesting. Red harvesters are not nocturnal, and they are sensitive to very hot sunlight. They are in the desert, so if they want to survive they have to start their foraging pattern very early in the morning and cease foraging operations around midday, when the sun heats the soil to temperatures above 52ºC (~125F). Yet, another species, the *Aphaenogaster cockerelli* is even less resistant to hot soil, but evolution gifted them with sensorial organs proper for nocturnal foraging. These two species share the same food supplies, and if they have nests near to each other they may compete for food. The *Aphaenogaster* uses a very interesting trick, sometimes at the end of their foraging cycle when the sun is about to shine, they cleverly block the entrance of the red harvester nest. The blocking itself is not a problem for the red harvesters, which have such amazing reconstruction abilities. The strategy of the competing species is that by blocking the entrance of the nest, the sunlight will only enter the red harvester nest when the sun is higher in the sky, delaying the start of the foraging cycle of the red harvesters and therefore limiting the amount of hours they will collect food; by doing that, more food will be available for the *Aphaenogaster* in their next foraging cycle.

**High Availability**

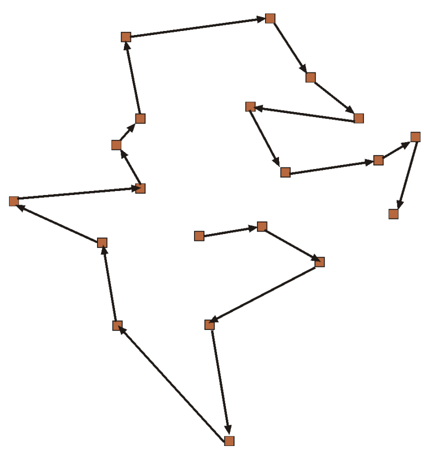
Gordon's experiments [8] also shown that ants may switch tasks, although unusual. It is normal that ants will keep the same task attributions from one day to another. There are basically 4 types of tasks a worker ant may perform: foraging, patrolling, maintenance work and midden work. If a nest disturbance is caused in such scale that a new demand for maintenance workers is created, then other ants assigned with other tasks will switch over and perform nest maintenance.

The notion that nature is very efficient is very intuitive for anyone that has a minimal knowledge about biological processes. We certainly wouldn't expect that a certain colony, especially in the middle of the desert where food is scarce, would have a number of idle individuals. Studies [8] have shown that some species of ants will let a great number of ants inside the nest just sitting idle with no particular task assigned to them. In a 10,000 elements colony, it is expected that only 3,000 ants perform external work, and there is not enough tasks to perform inside the nest to justify an army of 7,000 ants. A theory that helps explain such idleness is that nature itself has taught the ants to always keep a contingency of reserve ants for eventualities such as floods and other natural events.

**Brownian movement and Navigation**

In "*Matthews & Matthews 1942*" [2], spatial orientation is defined as "*[…] the self-controlled maintenance or change of an organism's body position relative to environmental space. It occurs when certain stimuli in the environment elicit a responsive sequence of behaviors that results in a nonrandom pattern of locomotion, direction of body axis, or both.*" In a natural habitat, ants are overwhelmed with stimuli presented all around, and great part of their sensorial system is dedicated to filter only those that are really important to their tasks. Typical stimuli found in nature can be classified in six major types of stimulus: heat, magnetism, light, gravity pressure and chemicals, being the latest a very important one for ants.

We can only infer that if we deprive an ant from all stimuli except the gravity, they will start showing a random pattern of locomotion. If stimuli provide orientation, then the lack of stimuli provides not the absence of locomotion, but brings an arbitrary pattern of locomotion. A simple experiment can be performed to show this theory: place only one ant in a surface free of any material or smell, and then observe what direction the ant will take. Much probably the ant will not follow a given direction for much time, and will show a pattern very similar to the one shown below:



Observing the illustration above, we see that lack of external stimuli incite a ceaseless random movement in the locomotion pattern of the ant; very similar to the one notably observed by Robert Brown in 1827 and named after him "Brownian Movement" [6].

In the other hand, ants seem very determined when they sense a pheromone or food around. Even when we obstruct a pheromone trail they will find the way around and continue their trail. In the real world ants, the sequence of movements observed in an ant is related to what task it is performing. While patrolling ants show a locomotion pattern around the nest similar to "*Brownian Movement*", maintenance and midden workers do not adventure to go very far from the nest entrance, and foragers leave the nest more or less in a straight line, even in the absence of previously deposited pheromones, as if they already new where their food was.

The notion that ants navigate only by means of stigmergetic communication is false and overly simplistic. Ants do have other sensorial organs in their body and they use them simultaneously to navigate around the nest. Adult ants have one or two types of eyes. The most complex type is a pair of compound eyes in each side of their heads composed of many facets usually in hexagonal shape. Depending on the ant species, there are 100 to 600 facets in each eye [9]. Comparing this number with other species like the Honey bees of wasps, ants have a very limited visual perception. Ants also have their bodies covered with sensitive hairs that may feel certain vibration frequencies, direction of gravity and wind. The most important sensorial organs though are the chemical sensors, usually installed on their antennas. They also communicate by means of an intricate combination of cricket sounds and antenna contact. All of these sensors suggest that chemical impulses are not the only information ants use to navigate. Some species use visual clues like environment marks to remember a path, others use a source of light (light-compass orientation) or even use the hair to sense gravity and slopes. Pheromone sensing is only one more hint they use.

**Pheromones and Foraging**

Pheromone is the generic name for any endogenous chemical substance secreted by an organism to incite reaction in other organisms of the same specie. Insects are known to make more use of pheromones for diverse tasks such as reproduction, alert, identification, navigation and aggregation [7]. They are released from several exocrine glands, usually located in the abdomen of the ant (red harvesters for example have 14 different glands [8]). Once they are released, the chemical structure of the pheromone allows that the molecules of the component be expelled into the air. If the air around the pheromone were still, a virtual sphere of around 15cm of diameter containing a decreasing concentration of matter towards the extremity of the sphere would form. Because in nature it is very difficult to find still air, a cone of spread matter would run down wind. Usually, a concentration of pheromones left by ants will completely evaporate in 100 seconds [9]. The ants' antenna is the principal agent for detecting pheromones; it contains several chemo-receptors that will trigger a biological reaction if the sum of all action potential (matter concentration) exceeds a threshold. The same way we can identify the source of a sound because of the different sound intensity on each one of our ears, ants can distinguish the direction of the pheromone source because they have two antennas. In "Matthews and Matthews, 1942": 186 [2], studies have shown that ants with one amputated antenna have difficulties following a pheromone trail, and if both antennas are extracted, they will loose the ability to communicate through pheromones.

Different types of ants have different strategies for foraging. Most of them will have some selected individuals assigned the task of scanning the environment around for available food. As soon as they leave the nest, they will usually take one direction and explore a given slice of land. Behind them, a pheromone trail is left, that will be used by other ants if the foraging ant succeeds finding food. Foragers that choose shorter paths will return earlier to the nest, therefore depositing more pheromone into that trail. Ants leaving the nest will probabilistically choose trails that have a higher concentration of pheromones, thus increasing it even more (autocatalytic behavior).

For a long time, it was believed that pheromone trails were polarized, as experiments lead to believe in this theory. If an ant is extracted from its original course in the pheromone trail and then replaced a few meters away, they will probably stumble at first but eventually they will find the direction they were following originally. This behavior if not studied with proper scientific methods would indicate that the trail itself would somehow indicate a sense of direction. Many believed that ants could detect the gradient of pheromone evaporation and therefore obtain the direction it was deposited in first place. Dr. Bethe [4] performed an experiment that proved that ants use a series of other senses while navigating, even if following a pheromone trail. The experiment consists in letting ants create a pheromone trail between points A (nest) and B (food source). Part of the trail was laid over a zinc turntable on a wooden plank. If the ant is midway from point A to B and the zinc turntable is spun 180º, the ant will also turn back and follow its original direction towards point B. This experiment proves that although pheromones play a very important role in navigation and colony ability to perform certain tasks, individual skills are equally important for colony survival.

## 2. Existing Research

Several researches have been made lately on ant algorithms, and the main character in this effort is the Italian Marco Dorigo et al [10-22]. His first work in ant algorithms was produced in his Ph.D. thesis in 1992 and the proposal of the Ant Systems algorithm. Dorigo follows a line of research that applies the concept of cooperative agents in solving complex combinatorial problems such as the *traveling salesman problem*, the *quadratic assignment problem* and others. Since 1992, Dorigo and his colleagues achieved many advances in solving a number of different combinatorial and optimization problems, combining different techniques inspired by the ant metaphor.

Ant algorithms are often compared with other evolutionary approaches such as Genetic Algorithms, Evolutionary Programming and Simulated Annealing. It is important to remember that Ant algorithms are non-deterministic and rely on heuristics to approximate to a sub-optimal solution in cases where the number of combinations is extremely huge and impossible to calculate using a deterministic algorithm. As stated in earlier studies [15], there is tentative classification of heuristic algorithms that are inspired by nature, namely "heuristics from nature". Classification of such algorithms is based on four characteristics of how they try to solve the problem:

a) constructive vs. improving algorithms;

b) non-structured vs. structured space;

c) single solution vs. population solution;

d) memory-less vs. memorizing algorithms;

Dorigo's group of study is available online: [*http://iridia.ulb.ac.be/~mdorigo/ACO/index.html*]. Since 1998 a biannual conference on Ant Colony Optimization is organized in Bruxelles, Belgium and attracts researchers of all over the world. Most of the concepts that will be presented in this section follow from his work.

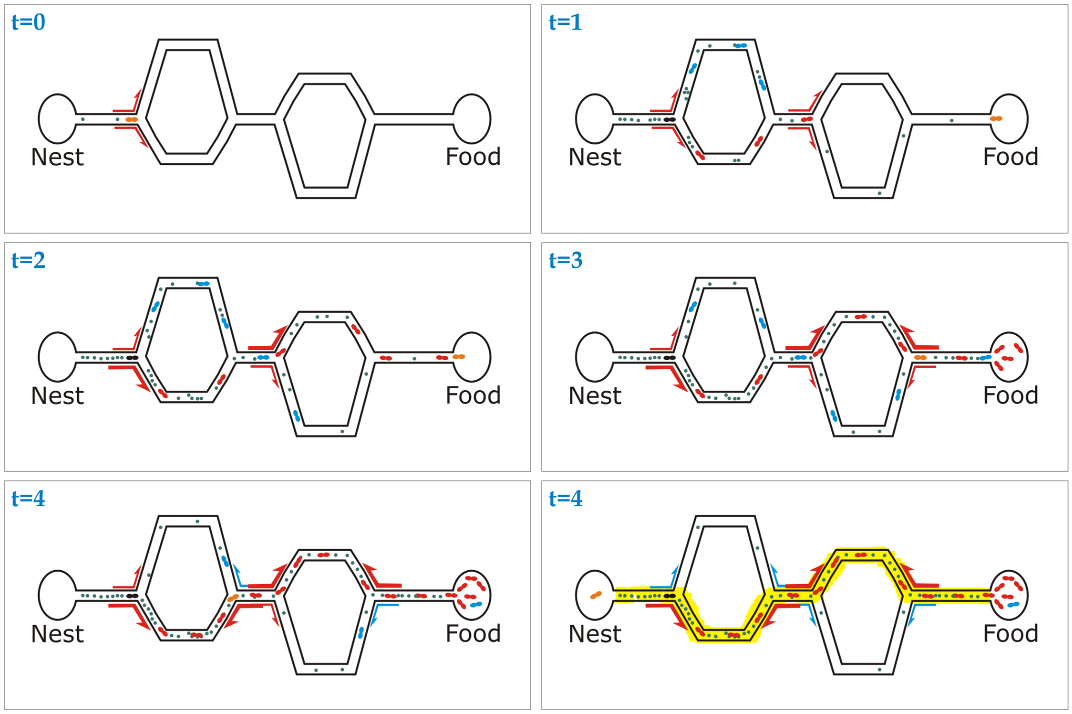



***Figure 1:*** *Arrow thickness represents probability of ants choosing one path over another. (t=0) Foraging ant chooses the path based on a 50% probability; (t=1) Follower ants also choose their path on a 50% probability; (t=2) Ants that choose the shorter path get the food faster; (t=3) First forager is coming back to the nest, because more ants completed the shorter path, a greater pheromone concentration will attract the first ant to that path; (t=4) Following ants choose the shorter path with a higher probability as more and more ants choose the same path; (t=5) After some time of this autocatalytic process the probability of ants choosing the longer path is very small*

Other lines of research with ant algorithms are in the area of computer vision and self-clustering. *Vitorino Ramos* [23-25] from Portugal has made significant advances in this area. His work may also be reached online at [*http://alfa.ist.utl.pt/~cvrm/staff/vramos/*]. On a higher level but still in the area of evolutionary algorithms and brought by the American wave of Complex Adaptive Systems, Lewis and Lawson [26-28] research a framework for emergent fluid cognition architectures. One very promising application of this framework is made using paradigms inspired by the ant colonies such as environment interaction and stigmergetic activity.

In the next few sections, we present an overview of the current methods inspired in biological ant societies applied to real world problem solving.

## 2.1. Ant Systems

Ant Systems was the first attempt to use the natural metaphor of ants to solve a hard combinatorial problem as the traveling salesman problem (TSP). The main characteristics of Ant Systems are:

- Autocatalytic – The system uses positive feedback as a way or auto-reinforcement
- Distributed computation – A number of agents are searching for the best solution
- Constructive heuristics – A "greedy force" that will balance ants' decisions between shorter paths or more paths with more pheromone

The Ant System algorithm is biologically inspired on the foraging pattern of ants. Natural ants when following a pheromone trail decide where to go next based on the concentration of pheromones on a given direction. Deneubourg [29] performed an experiment with real world ants that consists of a trail leading from the nest to food location that at certain point branches in two paths of equal length, that unify into one trail again shortly ahead. In a controlled environment, ants in search of food would follow that path and then would have to decide which branch to take. The first ant have no additional information to base its decision, so it just chooses any one of the two at random. Other ants following will choose any one of the two branches due to an initial random fluctuation. When the first ant is coming back from the food location towards the nest, it again will randomly choose any one of both trails because the amount of pheromone in the two trails will be very similar due to the initial random fluctuation and that they have the same length. The next experiment, known as double bridge made things very clear. Again, the ants are in an artificial controlled environment where they only have one path from their nest to a food source. This time, there are two bifurcations in sequence (fig 2), but unlike the first experiment, one branching path is shorter than the other. Initially the situation will be the same as the binary bridge experiment, but when the first ant is returning from food to nest, the concentration of pheromones in the shorter path will be stronger, simply because the flow of ants using that path was greater due to the length difference. Ants that chose that path will get to the unification point sooner that the ones who chose the longer path. This autocatalytic process starts to repeat over and over, and soon almost all ants will be choosing the shorter path over the longer one.

Although TSP was its first application, Ant System is not an algorithm specialized only in TSP, therefore other algorithms specialized in TSP may demonstrate a better performance. Also, artificial ants are only inspired by biological ones. Some distinctions do exist: the artificial ants have some memory (tabu list) in order not to visit cities already visited in a cycle. They not always follow pheromones, actually they will choose between a certain concentration of artificial pheromone and a shorter path to the next city based on a probability formula.

Ant System was born after two less successful algorithms, *ant-density* and *ant-quantity*. In these two algorithms, ants would lay out pheromone on the trail while walking through it (online step-by-step). One benefit to this approach is the reduction of the search space. After some iterations, branches that were not visited too often would be removed from the searching space, decreasing the average node branching of the problem.

In Ant System, pheromones are laid in the arcs at the end of iteration, and the amount of pheromone in the trails is calculated using the following formula:

$$\tau_{ij}(t+n) = \rho.\tau_{ij}(t) + \Delta\tau_{ij} \tag{1}$$

The amount of pheromone (τ) in the edge(i,j) at the end of one tour (t+n, assuming the graph has n cities) is calculated by first applying an evaporation coefficient (ρ) to the initial pheromone amount at instant **t** plus a new amount of pheromones calculated from all k ants that passed through the edge (i,j):

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{2}$$

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_n} \text{ if k - th ant uses edge(i, j)} \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

Q is a parameter that specifies the amount of pheromones ant k has to distribute through its trail, and L is the tour length of ant k. It becomes clear that ants with minimum tour length will deposit a greater amount of pheromone on edges pertaining to its path, while longer paths will dilute the pheromone amount among several edges of the graph.

Individual ants choose a new path based on this following formula:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{(\tau_{ij}(t))^{\alpha}.(\eta_{ij})^{\beta}}{\sum\limits_{k \in allowed} (\tau_{ik}(t))^{\alpha}.(\eta_{ij})^{\beta}} \\ 0 \text{ otherwise} \end{cases} \tag{4}$$

This formula means that the probability of a digital ant "k" to choose a path (i,j) depends on both the amount of pheromone ($\tau$) on that edge and the distance ($\eta$) from i to j. The parameters $\alpha$ and $\beta$ control how important each parameter will be in the probabilistic decision. Note that not all edges leaving from "i" to the next neighbor are allowed. The tabu list keeps a list of all edges already visited by the k-th ant and cannot be visited again by determination of the TSP constraints.

After performing some experiments, Dorigo et al in [12] showed that the stigmergetic communication really influences the overall solution of the problem. Actually, they found out that a balance between pheromone and greed heuristics is fundamental for good results. If no synergistic effect is used, the algorithm is trapped in some local maxima and compare to other greedy algorithms not finding very good solutions. In the other hand, if too much importance is given to pheromones, then the artificial ants will tend to quickly converge to one solution without exploring other alternatives, entering a stagnation state.

Although these formulas are fitted to TSP, the same concept may be adapted to use in different optimization problems. In order to implement an ant system algorithm for a problem, the same must have a few characteristics:

- The problem must have an appropriate graph representation that allows search by multiple agents;
- It must allow the implementation of an autocatalytic process (positive feedback);
- Some definition of heuristic that allows a constructive description of the solution must exist (greedy force);
- Constrains should be defined;

Ant System is the first attempt to use the ant colony metaphor to solve a NP-Hard combinatorial problem. The following sections will demonstrate some evolutions based on this concept.

## 2.2. Ant-Q

Ant-Q is a first step trying to implement reinforcement learning using the Q-Learning method. A complete explanation of Ant-Q algorithm plus an experimental study of the application of Ant-Q on TSP including a performance comparison between AS (Ant System) and Ant-Q is presented on [11] and [22].

Ant-Q still relies on two parameters alpha and beta to control the influence of greedy heuristics (path visibility) and a *pseudo-random-proportional* action rule, very similar in concept to the pheromone formula of section 2.1. Actually, the authors of Ant System and Ant-Q promptly admit that the pheromone updating formula of Ant System can be interpreted as one type or reinforcement learning. The fundamental difference between AS and Ant-Q is that only the best ant (the one that found the shorter path) gets to deposit pheromones in its trail.

Ant Colony Systems (ACS) is an improved algorithm based on Ant-Q and will be further studied in the next section.

### 2.3. Ant Colony System (ACS)

A good explanation of Ant Colony System (ACS) can be found in Dorigo and Stutzle [18] "ACO Algorithms for the Traveling Salesman Problem" and in Dorigo and Gambardella [21] "*Ant Colony System: A cooperative learning approach to the Traveling Salesman Problem*". ACS is an evolution on the line of algorithms first proposed to generate good solutions for the TSP. It follows from the Ant-Q, which implements a Q-Learning method of reinforcement learning and has the following distinctive characteristics over its predecessors:

- It has a more aggressive action choice rule
- Pheromones are added only to global best tours
- When ants choose an edge from i to j, it remove some pheromones from that arch

Since ACS is simpler and most efficient than Ant Systems and Ant-Q, it is the preferred algorithm by the authors.

The criteria used to calculate the probability of one ant k to move from city i to j is calculated in the same way of AS (formula 4), a product of pheromone amount in edge (i,j) and the length of edge (i,j). The pheromone updating formula is slightly changed:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \rho.\Delta\tau_{ij}^{gb}(t) \tag{5}$$

Unlike in AS, ACS pheromone updating formula is applied only to edges pertaining to the global best tour. Once more, ρ represents the pheromone evaporation parameter. The authors note that although there is no significant performance improvement of ACS over AS for smaller problems, for larger instances of TSP the global-best tour updating formula gives much better results.

Another improvement over the Ant-Q is how they handle the local pheromone trail update. At each step, ants decrease the amount of pheromone of that arc in order to make is less desirable to following ants. While this has no connection to biological ant's behavior, it does help avoid stagnation.

$$\tau_{ij} = (1-\varepsilon).\tau_{ij} + \varepsilon.\tau_0 \tag{6}$$

Formula (6) in ACS is almost identical to Ant-Q, except that $\tau_0$ is a parameter that replaces a few calculations. As demonstrated in [18] and [21], this substitution causes no harm to the algorithm effectiveness, but the reduction in calculation reduces the complexity of the problem and increases the performance of the algorithm.

### 2.4. MAX-MIN Ant System

MAX-MIN is very similar to Ant System; actually the solutions are constructed exactly the same way. As stated in [18], the main difference over Ant System is:

a) After each iteration only the best ant is allowed to deposit pheromones in the trail following the ACS model;

b) Pheromone strength is bounded by an upper and lower limit (thus MAX-MIN) to avoid stagnation;

c) Trails are initialized with the highest possible amount of pheromone to incite high exploration of trails at the start of the process.

At the end of each iteration all pheromones are decreased because of the evaporation coefficient but the pheromones in edges pertaining to the best solution are increased instead. The pheromone upper boundary helps avoid search stagnation by preventing only one trail to accumulate high values of pheromone. By limiting the amount of pheromone in a given trail, the probability of an ant choosing that trail is also being limited.

This algorithm was successfully applied to TSP [18] and the Quadratic Assignment Problem [25].

### 2.6. Ant Rank Algorithm

Ant Rank is thoroughly explained in [18] and it is a slightly variation of some elitist variations of Ant System. At the end of each iteration the global best is used to update pheromones. Additionally, a rank of best ants is kept at all times and a number of them are allowed to deposit pheromones while walking the trail. The ants are sorted by their current solution length, and only the very first *n* ants are allowed to update the pheromone trail. The action choice rule is identical to the AS.

Comparing $AS_{rank}$ with AS, Genetic Algorithms and Simulated Annealing, $AS_{rank}$ performed significantly better than the others.

### 2.7. Ant Routing

The algorithms discussed here so far are concerned with static combinatorial optimization problems. Static in a sense that cities will not move from one place to another while the search for a shorter path is going on, if to problem to solve is TSP. Some other problems are a moving target, and fundamental problem characteristics change during the course of the algorithm. These problems are named dynamic combinatorial optimization problems.

Although more complicated than the already very hard problems such as TSP, Quadratic Assignment Problem and Job-Shop Scheduling to name a few, dynamic problems are very important ones to solve as our world is becoming more and more virtual, therefore more dynamic.

Communication networks are the best example for such problem, where the problem is to find the best path from a sender and a recipient. The best path criterion depends on the nature of the problem. If the subject is a wide communication network such as the internet, the best path may be the one that chooses paths that combines higher bandwidth (static) and traffic information (dynamic). In telephony applications, the best route may be the one that uses switches with a greater number of available lines. These networks can be classified in connection-oriented networks [19] and connectionless network routing. In the connection-oriented networks, packets of information follow the same pre-defined route (i.e.: telephony networks), while on connectionless routing networks data packets may take different routes to reach their destination (i.e.: internet). Ant Colony Optimization was successfully applied to both problems in recent research. The analogy between ants and data packets is clear as they must travel across the network from a source to a destination node with the higher possible transmission speed.

Schonderwoerd et al [30], [31] was the first attempt to apply the ant metaphor to such problem. Their algorithm, known as Ant Based Control (ABC) was applied to a model of the British Telecom telephone network. One of the main differences is the implementation of a vector of pheromones where each element of the vector tells how desirable that connection is to carry the telephone signal to the destination related to that vector element. If the graph that represents the connection network has $n$ switches, then each edge of that graph that connects switch $i$ to $j$ will have a pheromone vector of $n$ elements. In ABC, ants only deposit pheromones online, differently from the approach of depositing pheromones only at the end of an iteration of Ant System. Also, ABC only uses pheromones for deciding the next path to take, not implementing any type of greedy local heuristic such as shorter path length in the case of TSP problem.

Other directions of ant routing research even include genetic algorithms to evolve the mixture of heuristic and pheromone parameters of the ant decision formula (ASGA – Ant System plus Genetic Algorithm).

Several studies are being made at this time to address the problem of connection-less communication network, a very dynamic problem. Included in this category are data networks (LAN, WAN, Internet, ATM) where current traffic conditions vary according to a number of parameters. This area of research is still very fresh, and even to this date new results are showing up. Dorigo et al. developed several versions of AntNet, an algorithm based on Ant Colony Optimization for distributed adaptive routing in conection-less data networks plus some concepts drew from ABC. In Ant-Net for example, pheromones are laid only after a path is build. Ants in this case are much similar to network pings, as the time from source to destination plays a very important part in the amount of pheromone that is deposited in the ant's path. The greedy heuristic is calculated according to current traffic in nodes leaving current position. For instance, if the traffic from current node to its neighbor is high, heuristic value should be low, whilst if traffic is low, heuristic value should be high. As in other traditional ACO algorithms, one ant decides which path to take by a probabilistic formula that is balanced by two parameters $\alpha$ and $\beta$ that regulate the bias towards pheromone and greedy heuristics. Several other versions of AntNet are still in development or were just recently published. AntNet-FA uses a concept of "flying ants" while AntNet-FS is directed to multi-path search. Dorigo et al. claims that results of AntNet are so far excellent, showing superior performance in terms of throughput and packet delays.

## 2.7. ACO Meta Heuristic

After years studying ant algorithms and its applications on optimization problems, Dorigo et al. came up with a basic framework that is applicable to a variety of problems. They named this framework as "ACO Meta Heuristic". A detailed explanation of it is contained in [10], including pseudo-code for the framework.

Basically, the ACO Meta Heuristic is the generalization of Ant Systems and subsequently algorithms. It is an attempt to set scope boundaries and implicitly defining what types of problems the framework can be applied. The explanation of the method in [10] is an abstract overview of all the characteristics of ant algorithms without having a specific problem attached to it.

However, for the first time the concept of *Daemons* was introduced, where an outside monitor would observe the behavior of the ants and collect useful global information to deposit additional pheromone information or apply local optimization procedures specific to a certain problem. The *daemon* would work as a supervisor that has specific knowledge about a problem and helps the ants choosing good solutions or not allowing them to deviate to illegal solutions.

## 2.8. Application in Optimization Problems

As stated earlier in this paper, Dorigo et al. are the pioneers in the application of ant algorithms into optimization problems, with first results of researches dating back to 1991. The field is still evolving, and the most recent studies in development are on the field of communication networks routing.

A summary of applications of ACO algorithms and its applications was extracted from [10] and reprinted in Table 1.

| PROBLEM NAME | AUTHORS | YEAR | MAIN REFERENCES | ALGORITHM NAME |
|---|---|---|---|---|
| Traveling Salesman | Dorigo, Maniezzo & Colorni<br>Gambardella & Dorigo<br>Dorigo & Gambardella<br>Stützle & Hoos<br>Bullnheimer, Hartl & Strauss | 1991<br>1995<br>1996<br>1997<br>1997 | [32, 16, 12]<br>[22]<br>[20, 21, 33]<br>[34, 35]<br>[36] | AS<br>Ant-Q<br>ACS & ACS-3-Opt<br>MMAS<br>ASrank |
| Quadratic Assignment | Maniezzo, Colorni & Dorigo<br>Gambardella, Taillard & Dorigo<br>Stützle & Hoos<br>Maniezzo & Colorni<br>Maniezzo | 1994<br>1997<br>1998<br>1998<br>1998 | [37]<br>[38, 39]<br>[40]<br>[41]<br>[42] | AS-QAP<br>HAS-QAP[a]<br>MMAS-QAP<br>AS-QAP[b]<br>ANTS-QAP |
| Job-shop Scheduling | Colorni, Dorigo & Maniezzo | 1994 | [43] | AS-JSP |
| Vehicle Routing | Bullnheimer, Hartl & Strauss<br>Gambardella, Taillard & Agazzi | 1996<br>1999 | [44, 45, 46]<br>[47] | AS-VRP<br>HAS-VRP |
| Sequential Ordering | Gambardella & Dorigo | 1997 | [48] | HAS-SOP |

## 3. Conclusions and Future Work

In this paper we presented the main algorithms and applications of ant algorithms, as well as a brief discussion on biological ants, the inspiration for ant algorithms.

Ants are very simple creatures with a really low cognitive capacity that does not make great realizations by itself. Instead, the collective body of the colony is capable of numerous complex tasks such as nest construction, nest maintenance and food gathering. They accomplish such amazing feats not by efforts of one individual or another but from massive interaction which makes such behavior "emerge". It is exactly the emergent behavior that is so interesting for computer science. Since the establishment of AI, one of the main challenges computer scientists face is how to represent problems in order to create algorithmic solutions. Very advances have been made in the field, but brittleness is always one of the products that limit the generalization capabilities of such solutions. At least apparently, ants are not concerned with representation; they simply act in the presence of absence of a given stimulus.

The work of Dorigo and colleagues is the most important reference on the field of ant algorithms, but it is mainly focused in solving combinatorial optimization problems, as we saw in this paper. Current research by Dorigo's group involves dynamic problems, as the effective routing of data packets through the internet using the shortest possible path. We should keep in mind that on communication networks such as internet, the physical length of the path linking two points is not as important as the time one data packet takes to travel from point A to B. Travel time is highly affected by traffic conditions of segments of that path, and may change from hour to hour. Finding the shorter path is not a trivial task.

Other researchers have been using the same metaphor to solve other problems. *Victorino Ramos* [23, 24, 25] is currently engaged in the application of ant algorithms to image processing, more specifically to image segmentation and clustering algorithms. Lewis and Lawson [26, 27, 28] are part of the Complex Adaptive Systems effort to find new ways to draw emergent behavior out of computer algorithms. Their current work is on a generalized framework (Starcat) based on the concept of fluid reasoning first introduced by CopyCat. To demonstrate the generality of their architecture, they came up with AntCat that borrows some behavior from biological ants. Merloti, the author of this paper is working on the AntBox, an ant simulator that tries to reproduce ant's behavior in digital environments.

There is a great expectation in the field of Artificial Intelligence that emergent systems will fill a gap left by traditional symbol based AI, where learning and dealing with new situations is always a huge challenge. Ant algorithms are one of such promising approaches, and there is still much work left to be done.

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